# Selling Cookies

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Recent developments in data collection and processing online.

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Welfare effects, regulatory implications depend on:

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- 2. How should a data provider price its information?
- 3. How does (data) market structure affect the equilibrium price?
- 4. Implications for related markets (e.g. advertising).

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Endogenous information structure: targeted vs. residual users.

Step 2. Finish

Thank you for providing your online preferences using the BlueKai registry! This simple 3-step process will put you in control of what some marketers know about you. Based on partner feedback, below is a list of your online preferences for topics of interest. Please review and edit by clicking "Remove" next to a particular preference. Then, click on "Continue" to select benefits.



Please note that preferences are noted based on collective activities from your computer. If your computer is shared, this may reflect interests from other members of your household. To see how this works, visit www.welovesports.us (a fictitious sports site that will appear in a new window), and refresh this page.

Continue

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E.g., "Overome Tours" may buy the IDs of:

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DMP charges a linear price per unique user or per use.

# Consumers, Advertisers and Matching

Unit mass of user characteristics i and firms (advertisers) j.

Match value (potential surplus)  $v(i,j) \in V$ .

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Characteristics i unobservable: targeting requires user-level data.

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Data about individual users sold at a constant linear price,

$$p(A_j) \triangleq p \cdot \mu(A_j).$$



# Selling Access to a Database

## **Selling Cookies** (today's paper):

- Unit of sale: individual queries (realizations of a r.v.).
- Linear price per query.
- More elaborate market environment.

## **Selling Experiments** (tomorrow's paper):

- Unit of sale: arbitrary information structures.
- Menu pricing of information.
- Abstracts from source of value.

# Advertising as Matching

Advertisers generate value by choosing **match intensity** *q*:

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q =consumer awareness probability;

m(q) = required amount of advertising space;

c =unit price of advertising space.

### Choice of Information Structure

Suppose firm *j* buys cookies in the *targeted set A*.

Complete-information action  $q^*(v)$  for each  $v \in A$ .

Constant action  $q^*(A^C)$  for all  $v \notin A$ .

Each firm chooses a targeted set A to maximize

$$\int_{A} \left(\pi\left(v, q^{*}\left(v\right)\right) - p\right) dF\left(v\right) + \int_{A^{\mathsf{C}}} \pi\left(v, q^{*}(A^{\mathsf{C}})\right) dF\left(v\right).$$

<u>v</u> Match values

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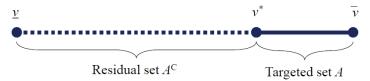
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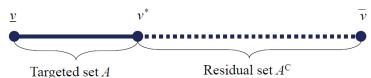
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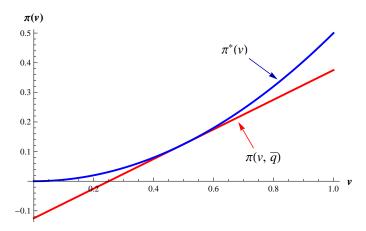
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"Negative Targeting"



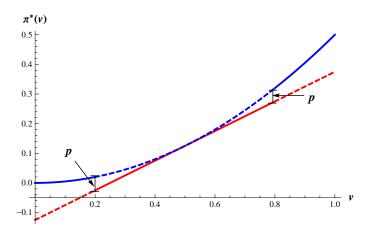
#### Prior- and Full-Information Benchmarks



Linear profits under prior information.

Strictly convex profits under full information.

## Positive and Negative Targeting



p = marginal value of information.

## Optimal Residual Set

#### Proposition (Convexity of Residual Set)

For any c, p > 0, the optimal residual set  $A^{C}(c, p)$  is a non-empty interval  $[v_1(c, p), v_2(c, p)]$ .

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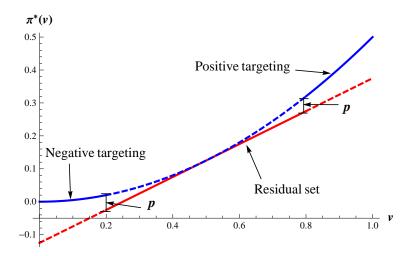
#### Proposition (Positive and Negative Targeting)

With symmetrically distributed match values and quadratic matching costs, the optimal residual set is given by:

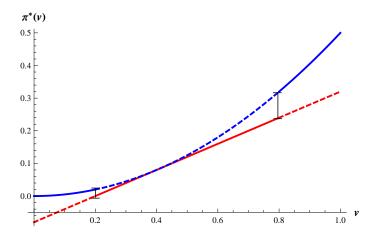
$$A^{C}(c, p) = [\mathbb{E}[v] - \sqrt{cp}, \mathbb{E}[v] + \sqrt{cp}].$$



## Joint Positive and Negative Targeting

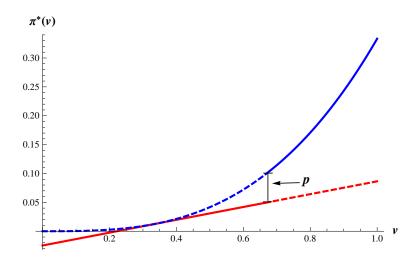


## Decreasing Density f(v)



Value of information highest "at the top" of residual set.

## Positive Targeting



Optimal targeted set is an interval,  $A = [v^*(c, p), \bar{v}].$ 

## Demand for Data and Advertising: Summary

Positive vs. negative targeting vs. both depends on:

- advertising (matching) technology;
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#### Demand for advertising:

- Differential spending levels within targeted set.
- Uniform (positive) spending level on residual set.

#### The Data Seller's Tradeoff

Assume positive targeting is optimal,  $A(c, p) = [v^*, \bar{v}].$ 

A monopolist seller chooses the threshold  $v^*$  to maximize

$$\underbrace{\left(\pi\left(v,q^{*}\left(v\right)\right)-\pi\left(v,q^{*}\left(\mathbb{E}\left[\tilde{v}\mid\tilde{v}\leq v\right]\right)\right)\right)}_{\text{price}}\underbrace{\left(1-F\left(v\right)\right)}_{\text{quantity}}.$$

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Effects of expanding supply (lowering  $v^*$ ):

- 1. Lower marginal value of information (i.e. price) at  $v = v^*$ .
- 2. Lower match intensity with residual set  $A^{C} = [\underline{v}, v^{*}]$ .

Note: #2 partially compensates for #1.

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#### Proposition (Data Sales Fragmentation)

The symmetric equilibrium price with a continuum of data sellers  $\bar{p}$  exceeds the monopoly price  $p^*$ .

Result extends to n independent and exclusive data sellers.

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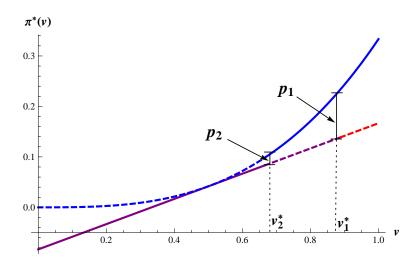
#### Proposition (Reach of the Database)

- 1. Then the advertisers marginal willingness to pay  $p(A; \beta)$  is increasing in  $\beta$  for all A.
- 2. (Under suitable conditions) the monopoly price is strictly decreasing in the reach  $\beta$ .

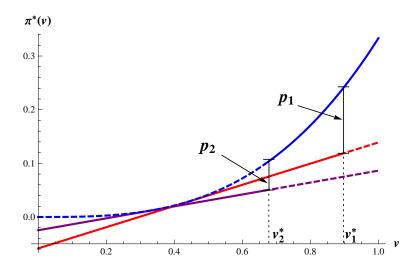
Low reach  $\beta \Rightarrow q^*(A^{\mathsf{C}})$  not responsive to A.

Lower incentives to expand supply of data.

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Market structure or data availability may limit composition effect.

## Concluding Remarks

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#### Extensions:

- Cross-market externalities: availability of data may increase equilibrium price of advertising space.
- Consumer surplus: advertising as matching (+) vs. division of total surplus (?).
- Value of privacy and endogenous data availability.